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School Quality, Exam Performance, and Career Choice*

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Abstract

The purpose of this paper is to examine the effects of school quality on performance in national exams and the career decision at age 16. We use micro data for the UK, which provides a rich set of variables on parental background, previous achievements, and community variables. We find that, conditional on school type, the pupil-teacher ratio has no effect on examination performance. The pupil-teacher ratio has an effect on the career decision at age 16 as to whether to remain in full time education beyond the minimum age, enroll in training activities, or join the labour market full time. This finding appears to be very robust, and sustains when school type variables, exam results, and ability are controlled for.

Keywords: School inputs, Educational Attainment, Training.
JEL-Classification: C35, I20, J24

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1 Introduction

In recent years, the effect of schooling input on educational achievement and earnings has been the subject of intensive research. Many studies seek to determine the effects of school quality variables on later earnings. A few studies take a more direct approach and try to estimate the effect of school input on examination success. The measures for school quality typically used in this literature are pupil-teacher ratios, teachers' salaries, or expenditures per pupil.

So far, the evidence on these effects is conflicting. The first systematic study has been performed for the US (Coleman et al. (1966)) and concluded that there are hardly any effects of school input. Some authors argue that most of the later research has confirmed that view, and that the benefits of increased spending on school resources are very limited (see, for example, Hanushek (1996), Betts (1995), Hanushek, Rivkin and Taylor (1996)). In a recent survey, Hanushek (1996) comes to the conclusion that three decades of research have shown that "school resource variations are not closely related to variations in student outcomes".

Others argue that this evidence is far from conclusive. Positive effects of school quality are found, for instance, by Johnston and Stafford (1973), Card and Krueger (1992), and Heckman, Layne-Farrar and Todd (1996). Card and Krueger (1996) summarize evidence which is largely supportive of the view that school quality is positively related to economic outcomes.

Hanushek, Rivkin and Taylor (1996) try to resolve this apparent conflict in the literature. They argue that two factors may be responsible for the positive effects of school quality on achievement: omitted variables, and aggregation. Omitting variables like family background, which have an independent effect on both the quality of schools attended, and later earnings, leads to a positive spurious correlation between school resources and performance. Furthermore, much of the work which is supportive for the view that school expenditures bear a positive effect on the student's achievement use data on an aggregate level. For instance, Card and Krueger (1992) use state average school characteristics. Hanushek, Rivkin and Taylor (1996) show that the omitted variable bias can increase if the data is aggregated. Altonji and Dunn (1996), however, still find positive effects of school inputs on wages. They use disaggregated data and solve the problem of unobserved background variables by using variations among siblings in high schools to control for family background. Goldhaber and Brewer (1998) use data from the National Educational Longitudinal Study. They find that some schooling resources do influence mathematics test scores. They further conclude that unobservable school quality factors are important, but not correlated with observable school quality variables.

We focus on the UK. While most studies in this field refer to the US, some studies for the UK have recently appeared. Harmon and Walker (1997) investigate the impact of school quality on wages. Dearden, Ferri and Meghir (1998) analyze the impact of school quality on wages and education level attained at age 33. Feinstein and Symons (1997) and Robertson and Symons (1996) analyze attainment measured by ability tests for primary and secondary school, respectively. The main purpose of this paper is twofold: we analyse the effect of school quality on examination performance and on the career decision taken at age 16. Our analysis of examination performance relates to the existing literature on school quality and school achievements. We are in a better position than most existing studies for the US due to the rich nature of our data set, which allows us to explicitly address the problem of omitted variables.

There are only few studies on the impact of school quality on the level of education achieved, although this clearly has important implications for education and training policies. In a recent paper, Card and Krueger (1996) argue that an increase in school quality induces students to attend school longer as a response to economic incentives created by a higher payoff to schooling, or because school is simply more pleasant. In fact, aggregate data suggest that school quality bears an effect on the length of education (see Card and Krueger, 1992). We think of ultimate educational attainment as the outcome of a stepwise decision process, and we focus on one step in that process. In particular, we investigate the effect of school quality on the decision to stay in full time education beyond the minimum required age, go into some type of training, or join the labour market.

Our data are drawn from the National Child and Development Survey (NCDS). It refers to a cohort born in 1958 in Britain and Wales. All the individuals in our sample sit their first public examinations at age 16. After that, they have to decide whether to join the labour market full time, enroll in some training scheme, or continue full time education. The data is unique since it provides an unusually rich set of variables, including family background information, school characteristics, previous achievements of the individual, community variables, and parental preferences about the child's education. Our main measure for school quality is the pupil teacher ratio on school level. This variable is a most visible measure of school quality and has attracted considerable attention in the recent public discussion both in the US and the UK.

Our results are interesting in several respects. We find that family background, working environment, as well as parental preferences, play a significant role for the academic performance of the offspring. The pupil teacher ratio has a significant and negative effect on the child's exam performance, conditional on parental background variables and indicators for previous achievements at age 7 and 11. Omission of previous achievement indicators leads to an inflation of the coefficient of our school quality indicator by a factor 2. The effect of the pupil teacher ratio becomes insignificant if we introduce school types as a further measure of school quality.

Again controlling for parental background variables and previous achievement, we find that the pupil teacher ratio is an important determinant for the career choice at age 16: pupils at schools with a lower pupil teacher ratio, are more likely to stay in full time education. When we introduce school type variables, the effect decreases in size, but remains significant. We check the robustness of our results for various model assumptions. We also estimate models conditioning on exam success, allowing for its endogeneity.

Our main conclusion in all model specifications is that school quality has a positive effect on the decision to continue full time education. This has important implications for overall educational outcomes. Our results add micro – based evidence to the findings of Card and Krueger (1992) that school quality has a positive effect on the length of education.

The paper is structured as follows. In the next section, we discuss the data used for the estimation. In section 3, we present the econometric model. Section 4 discusses the results, and section 5 concludes.

2 Data and Variables

Our data source is the National Child and Development Survey (NCDS). The same data source is used for several other studies on the UK on similar topics, such as Harmon and Walker (1997), Feinstein and Symons (1997), Robertson and Symons (1996), and Dearden, Ferri and Meghir (1998). The NCDS followed a cohort of individuals born between 3rd and 9th March 1958 (see Micklewright (1986) for a detailed description of these data). Of particular interest is the data recorded in the third and fourth sweeps of the survey (NCDS3 and NCDS4) and information collected in the Public Examinations Survey (PES), a follow-up survey to NCDS3. NCDS3 was conducted in the spring of 1974, and records extensive information about the respondents, such as educational and physical development, aspirations for the future, spare time activities etc., as well as much of the information usually gathered in household surveys. Similar information was also gathered for NCDS4 in 1981 when cohort members were aged 23. NCDS4 also contains further details on education and employment experience. We thus have an accurate picture of teenagers and their family prior to and after the choices made at the age of 16.

We take as our measure of academic success the number of Ordinary level (O' level) passes achieved by 1974.[1] Since NCDS3 dates from Spring 1974, we observe the cohort members when they are still in compulsory full time secondary education and a few

[1]In 1974, two sets of public examinations existed in Britain - Ordinary level examinations and Certificates of Secondary Education (CSEs). O' level candidates were graded on a scale of A - E, where C and above was considered a pass. For CSEs, results were graded from 1 to 5 and a Grade One was considered to be an O level equivalent. Therefore our number of O' levels includes CSE Grade One passes.

months before they sit their first set of public examinations, O' levels and Certificates of Secondary Education (CSE's), in June 1974. The PES conducted in 1978 has detailed information on the examination results of about 95% of respondents to NCDS3, obtained from the schools.

For information on school leaving decisions, we draw on NCDS4. This contains a month-by-month diary recording the economic activity from May 1974 to January 1982. We use the information recorded in February 1975 to see whether the cohort members were at the end of their sixteenth year, full-time at school, had a regular job, or were following a training programme.[2]

The data set used for estimation is based on a sub-sample of almost 4,000 cases out of the possible 11,602 who were traced at NCDS3, PES and NCDS4. Differences in the educational system in Scotland restricted our analysis to those teenagers living in England and Wales. A more significant factor was the problem of missing or incorrectly recorded information which contributed to the exclusion of some 7,000 observations from our data set. Information collected at the third sweep was retrieved from four separate sources (from the cohort member, from his or her parents, from the school that the 16 year olds attended and from the teenager's doctor) and many respondents failed to complete one or more of the questionnaires. The studies referred to above which use the NCDS data, faced the same problems and are based upon similar numbers of

[2]We classify all those who have any element of training associated with their job as being in the "training" category, in addition to those enrolled on full time training schemes. Thus, for example, an individual in part time employment and on an apprentice scheme would be classified as being in training, as would someone who was simultaneously on a government training scheme and in part time education.

Table 1: Descriptive Statistics

Variable	Description	Mean	Std Dev
Dep. Var.:			
C16	Choice of activity at end of 16th year:		
	Stay at school	31.20	
	Enroll on training scheme	30.47	
	Regular Job	38.33	
EXAM	Number of O' levels/CSE Grade 1s passed	2.34	2.91
Explanat. Var.:			
oldsib	Number of older siblings	0.428	0.642
yngsib	Number of younger siblings	1.202	1.243
paageft*	Age father left full-time education	4.012	1.733
maageft*	Age mother left full-time education	4.020	1.413
ptratio	Pupil-teacher ratio	17.133	2.298
loginc	Logarithm of household income	3.860	0.403
pawork	Father working	0.903	0.294
mawork	Mother working	0.691	0.462
paprof	Father's occupational class professional	0.057	0.231
modern	Teenager attends a secondary modern school	0.246	0.431
tech	Teenager attends a technical school	0.008	0.090
comp	Teenager attends a comprehensive school (non-selective state run)	0.530	0.499
grammar	Teenager attends a grammar school (higher ability state run)	0.149	0.356
indep	Teenager attends a private school	0.044	0.206
special	Teenager attends a special school (handicapped and special needs children)	0.020	0.140
singsex	Teenager attends a single sex school	0.266	0.442
intpar	Teacher considers parents to be interested in teenager's school work	0.745	0.435
paralev	Parents want teenager to sit A levels	0.252	0.434
paruniv	Parents want teenager to go to university	0.356	0.478
female	Teenager is female	0.500	0.500
room	With private room for studying	0.893	0.310
able7	Percent score on sum of age 7 maths and reading test	73.85	20.55
able11	Percent score on sum of age 11 maths and reading test	57.61	19.51
able16	Percent score on sum of age 16 maths and reading test	60.60	18.95
abs1	Absent from school for health reasons 1 week - 1 month (during year before examination)	0.351	0.477
abs2	Absent from school for health reasons 1 - 3 months (during year before examination)	0.066	0.248
abs3	Absent from school for health reasons > 3 months (during year before examination)	0.009	0.099
unemp(la)	Unemployment rate (Local Authority)	4.925	2.057
uman(la)	Percentage unskilled manual workers (Local Authority)	7.328	2.755

*: These variables are measured on a scale from 1 to 10; 1 denotes that the parent left school aged 13 or less, 2 aged 13-14 etc.

observations. Table 1 explains the variables used in our analysis and provides means and standard deviations.

3 School Quality and Educational Achievements

Our dependent variables are exam results and the choice at age 16 between continuing full time schooling, training, or a regular job. In this section we discuss the factors that drive these outcomes and the corresponding variables constructed from our data.

Educational outcomes of school children depend on a number of factors. The family background plays almost certainly a most important role, which affects pupil's achievements in various ways. In the tradition of Becker (1981), one may want to distinguish between financial and time resources allocated to the child. Financial resources may be used to choose better schools for the child, and to provide a more suitable environment for studying. Time inputs may consist of the time parents spend with the child for explaining homework exercises, for instance. However, not only is the amount of resources allocated to the child important for enhancing her performance, but also the efficiency of its use. For instance, better educated parents are likely to be more efficient when supporting the child with homework, and may provide more support for her academic development.

In the empirical analysis, we measure financial resources of the family by family income.[3] As a measure of time inputs, we use the labour market status of the parents, particularly of the mother. As measures for the quality of time, we include parental

[3] The income information in NCDS3 is recorded in a banded form. We constructed a continuous measure of income, taking into account all sources of household income, following Micklewright (1986).

education. Not only parental input affects the child's performance, but also the studying conditions. We include a variable which measures whether the child has a separate room in which to study. In families with more than one child, children are likely to compete for resources. Becker's (1981) work suggests that parental attention is reduced as family size increases. Hanushek (1992) finds that the birth order plays an important role for children's academic performance. We therefore include the number of older and younger siblings among our regressors.

When isolating the effects of school quality variables on academic achievement, not only do contemporary factors play a role, but also differences in previous academic preparations. Pupils with different previous achievements may, for instance, go to schools of different quality, and previous achievements should be included to isolate the effects of present school characteristics. We follow Hanushek, Rivkin and Taylor (1996) and use standardized test scores to control for these differences. Test scores also reflect differences in ability between children. We use combined test scores from attainment tests in mathematics and reading comprehension that respondents sat at the age of 7 and 11.

A further possible determinant for scholastic achievements is environmental factors, such as economic characteristics of the environment where the child grows up. For instance, attending a school in a working class environment could have some effect on the child's behaviour, keeping family background constant. The attitude of the peer group of all class mates towards the importance of education, may well have some influence on the pupil's behavior. Furthermore, it is possible that pupils' incentive to work hard for their exams is affected by future labour market prospects. We therefore include variables which measure the rate of unemployment, as well as the percentage of unskilled manual workers, on a local authority level.[4]

Parental interest in the child's academic performance may not be entirely captured by the above set of family background variables. Keeping wealth and education constant, parents may still differ substantially in their preferences regarding the education of their child. As has been emphasised by Hanushek, Rivkin and Taylor (1996), correlation between these preferences and school quality – which may depend upon the parents' choice, may lead to an upward bias of the effect of school quality if the parents' preferences are omitted. It is therefore desirable to include variables which capture the parents' interest in the offspring's educational career. We use a variable which reflects the opinion of the teacher on the parent's interest in the teenager's school performance, and variables which indicate whether the parents want the teenager to complete Advanced levels (A' levels) or to follow a University education.

Our quality measure is the pupil teacher ratio on school level. It is derived as the ratio of the total school roll and the number of full time equivalent teachers. Aggregation to school level avoids the endogeneity problem of class level ratios, which arises if weak pupils are assigned to small classes (see Card and Krueger (1996)). The pupil teacher ratio is likely to be related to the type of school the child attends. In the empirical analysis, we estimate specifications which use this ratio as the only measure of quality, and specifications which also include dummy variables which specify the type of school that the 16 year old attended in 1974.[5]

[4] This information is drawn from the 1971 census. The local authority data covers around 500 separate areas, and therefore relates to quite narrowly defined labour market areas.

[5] During the early 1970s, the tripartite selection-based system of grammar schools, secondary modern schools and technical schools was still being used in many local authorities, while in other areas, mixed ability comprehensive schools were already introduced (see Harmon and Walker (1997) for

The continuation decision after completion of the minimum required school education is a choice between full time education, activities with some elements of training attached, and joining the labour market full time. This decision should depend on similar factors as examination performance. Since it is taken after public examinations, a structural specification also conditions on the exam outcome. School quality may affect career choice directly, and in an indirect way via exam results. The direct effect could be caused by better decision making support in schools which allocate more resources to their pupils, or by peer pressure. Furthermore, pupils may use the efficiency of past education as a benchmark when planning their future career. If pupil teacher ratios increase this efficiency, then pupils who attended schools with lower ratios may react to the increased payoff by choosing further full time education. Finally, as pointed out by Card and Krueger (1996), increased school quality may make schools more pleasant, and induce children to stay on beyond the minimum required age.

The set of factors which affect examination performance and career choices alike may be summarised in the following equation:

$$O_i = f(F_i, E_i, T_i, S_i, \epsilon_i) \tag{1}$$

where i is the individual, O_i is the outcome variable, F_i are family background variables, E_i are environmental factors, T_i are variables which capture the attainment history of the individual, and S_i are variables which measure school quality.

The function f and the assumptions on the distribution of the error term ϵ_i reflect the choice of the model. The number of O' level passes obtained at age 16 ranges from

details).

0 to 9 and is zero for about 50 percent of all individuals. This suggests the use of a Tobit model. Since the outcome is always one of the integer numbers 0,1,...,9, other options are ordered probit (or logit), grouped probit, or some count data model like the Poisson or the negative binomial model.

The career choice after the exams will depend on the same types of factors as the exam results, and on the exam results themselves. The three alternatives, i.e. continuing full-time education ($C16 = 2$), going into a training programme ($C16 = 1$), or entering the labour force ($C16 = 0$), can be viewed as ordered and modeled by an ordered probit model. Alternatively, a multinomial logit can be used, not exploiting the ordering. The multinomial logit model is more flexible since it includes two linear combinations of the explanatory variables instead of one, but it imposes an independence assumption among choices. We use here a generalized ordered probit model, where one of the category boundaries depends upon the regressors. See appendix for the complete model. This model has the same degree of flexibility and the same number of parameters as the multinomial logit model. It avoids the independence of irrelevant alternatives assumption and instead uses the ordering of the alternatives. This seems to be more appropriate than unordered multinomial logit (or probit) in the current context. [6]

[6] See Pradhan and Van Soest (1995) for details and a comparison of the two types of models in a similar framework.

4 Results

Examination Equation

Table 2 presents tobit estimates, where the dependent variable is the number of O levels achieved.[7] The first column is a basic specification, which includes various family background variables, and the pupil teacher ratio. Most variables are significant (at the two-sided 5% level) with the expected sign. Both older and younger siblings affect exam success negatively, with older siblings being more important. This is in line with other studies which find birth order important for school success (Behrman and Taubman (1986), Hanushek (1992)). The effect of the mother working is negative, reflecting that a working mother spends less time to help the child. Children with their own room to study perform significantly better than others. The education levels of both parents are strongly positively related to exam success. In this specification, the pupil teacher ratio has a significant and sizable negative effect on the exam results: An increase in the pupil teacher ratio by one standard deviation decreases the number of O' levels achieved by about 0.7.

In column 2, we have included standardised test score variables which measure past performance. Hanushek, Rivkin and Taylor (1996) emphasise the need to control for past performance to isolate the effect of contemporaneous school quality variables. In the absence of these variables, if individuals with poor past performance select into lower quality schools, school quality indicators tend to be downward biased. Furthermore, past achievements may be determined by family characteristics which also effect

[7] Ordered probit or count data models led to qualitatively similar results. OLS results are also similar, but with higher significance levels in general.

current performance. The results in column 2 show that including past performance indicators changes the coefficient on the ptratio variable quite dramatically. The effect on exam performance drops by one half, but remains statistically significant. Furthermore, the effects of the other family background variables change as well. For instance, the effect of father's and mother's education drops by about one half. The effect of family income decreases, and becomes insignificant. This indicates that both school quality and past performance are positively related to family resources and parental background.

In column 3, we have conditioned on unemployment rates and the percentage of unskilled manual workers on local authority level, as well as on parental preferences regarding the offspring's future academic career. The local labour market indicators turn out to be insignificant, while parental interest variables have a strong and significant effect on examination performance. For example, conditional on parental and family background and the child's past performance, the parents' wish that the child attends university increases the number of O' levels achieved by 2.7.[8] Including these variables reduces the size of the variable PTRATIO only slightly, and it remains significant.

In column 4 we add school type dummies. The base category refers to secondary modern schools (lower ability public schools). The dummies for grammar schools, state run schools, and private schools are significant with the expected positive sign. Teenagers attending comprehensive (non-selective state run), technical, gram-

[8]Parental preferences are potentially endogenous: variables which are not observed in the data, but known to the parents, and affect parents' preferences about the child's career as well as the child's exam performance, may lead to an upward bias of the coefficients of the preference variables. Some of these factors should be captured by the past performance indicator variables able7 and able11.

Table 2: Exam Equation, Tobit Models

Specification	1		2		3		4	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
constant	-1.762	-1.68	-10.512	-10.31	-9.265	-9.25	-10.62	-9.29
oldsib	-0.872	-7.04	-0.548	-4.98	-0.462	-4.41	-0.464	-4.53
yngsib	-0.534	-8.45	-0.254	-4.40	-0.173	-3.17	-0.160	-3.00
pawork	1.721	5.45	0.292	1.11	0.236	0.95	0.297	1.22
paprof	0.948	3.20	0.877	3.22	0.618	2.42	0.579	2.34
mawork	-0.339	-1.99	-0.325	-2.14	-0.213	-1.48	-0.185	-1.31
female	0.521	3.53	-0.063	-0.48	-0.006	-0.05	-0.025	-0.21
paageft/10	5.602	9.61	2.563	5.89	1.608	3.86	1.441	3.53
maageft/10	4.334	8.98	2.783	5.36	1.625	3.28	1.595	3.27
loginc	0.763	3.35	0.319	1.61	0.022	0.11	-0.013	-0.07
room	0.945	3.69	0.607	2.64	0.455	2.07	0.400	1.86
ptratio	-0.307	-8.17	-0.150	-4.23	-0.116	-3.43	-0.090	-0.22
able7/10			0.469	9.62	0.358	7.72	0.304	6.62
able11/10			1.195	24.00	1.017	21.28	0.920	19.14
intpar					0.935	5.87	0.896	5.76
paruniv					2.710	16.50	2.443	15.01
parAlev					1.088	6.49	0.994	6.07
unemp(la)					0.009	0.23	0.004	0.08
uman(la)					0.001	0.04	0.003	0.10
comp							0.693	3.76
tech							1.137	1.87
grammar							1.916	8.13
indep							2.087	6.02
singsex							0.089	0.52
special							1.180	1.92
σ_{u_E}	4.102	58.60	3.025	60.54	2.929	58.44	2.78	55.62
Log-Lik.	-6956.16		-5020.47		-4849.52		-4740.31	

Table 2a: PTRATIO, various school types			
School type	N. Obs.	PTRATIO	STD
modern	947	18.25	1.69
comp	2021	17.13	1.58
tech	29	16.67	1.76
grammar	558	16.11	1.41
indep	178	14.69	2.80
special	78	13.21	4.17
singsex	1018	16.47	2.22

mar schools (higher ability state run schools) (variables GRAMMAR, or independent (selective non-state run schools INDEP) perform significantly better, relative to pupils in secondary modern schools.

The order of the effects of school types is reversely related to the pupil teacher ratio, as shown in table 2a. The coefficient of the PTRATIO variable decreases only slightly, but the standard error increases substantially, which is due to the collinearity between this variable and the school type variables. However, the effect of school type dummies is considerably larger than what we could expect as a result of mere differences in the pupil teacher ratio. For example, the average difference in PTRATIO between grammar schools and modern schools of -2.1, combined with the parameter estimate of -0.116 in column 2 would lead to an effect of 0.23, much less than the coefficient of 1.91 for grammar schools in column 3. Other factors, such as peer group effects (more intelligent class mates in better schools) or quality of teachers are apparently more important for exam results than the pupil teacher ratio.

To conclude, our results indicate that school quality, as measured by the number of pupils per full time teacher on school level, has an effect on exam performance, even after controlling for parental background, parental preferences, community variables, and the child's past performance. Omitting parental background variables and, in particular, past performance indicators, leads to a substantial inflation of the effect of the school quality variable. The effect of the pupil teacher ratio becomes insignificant if we add school type variables as an additional set of school quality indicators.

Career Choice

We first discuss probit estimates of the probability that a student decides to continue in full time education. We thus collapse training and school leaving into one alternative category. In table 3, we present the results.

The specifications we have estimated are the same as in table 2. They are reduced form estimations in the sense that we do not condition on exam success. We report the marginal effects of changing the regressors on the probability of staying in full time education, evaluated at the mean values of the regressors (reported in table 1). The results in column 1 show that family background variables are important for the staying on decision of the teenager. Pupils in larger families are less likely to stay in school, where, again, older siblings seem to matter more than younger siblings. The father's and mother's years of education have the expected positive impact on the child's probability to continue full time education. Family income is positive and significant. The effect of the variable PTRATIO is quite strong and significant. An increase of the variable PTRATIO by one standard deviation reduces the probability that the child stays on in full time education by 9 percentage points.

In column 2, we condition on the test score variables at age 7 and age 11. As for

Table 3: Full Time Education, Probit Models; Marginal Effects

Specification	**1**		**2**		**3**		**4**	
	Effect	t-ratio	Effect	t-ratio	Effect	t-ratio	Effect	t-ratio
cons	-0.229	-2.01	-0.789	-5.74	-0.589	-3.67	-0.675	-4.44
oldsib	-0.080	-5.85	-0.053	-3.57	-0.039	-2.62	-0.040	-2.65
yngsib	-0.030	-4.44	-0.023	-2.95	-0.011	-1.38	-0.009	-1.18
pawork	0.077	2.40	0.041	1.16	0.036	1.00	0.045	1.21
paprof	0.219	5.86	0.161	4.03	0.119	3.05	0.121	3.03
mawork	-0.012	-0.66	-0.014	-0.71	-0.003	-0.18	-0.002	-0.12
female	0.004	0.28	-0.027	-1.55	-0.018	-1.03	-0.021	-1.17
paageft/10	0.625	9.72	0.332	5.62	0.183	3.08	0.165	2.74
maageft/10	0.430	8.36	0.442	6.15	0.239	3.35	0.233	3.19
loginc	0.060	2.44	0.029	1.08	-0.022	-0.82	-0.030	-1.09
room	0.096	3.42	0.095	2.99	0.067	2.12	0.061	1.91
ptratio	-0.041	-10.03	-0.032	-6.68	-0.030	-6.23	-0.019	-3.54
able7/10			0.045	6.68	0.031	4.66	0.026	3.87
able11/10			0.073	11.01	0.049	7.31	0.041	5.91
intpar					0.064	2.81	0.059	2.57
paruniv					0.453	18.46	0.439	17.56
parAlev					0.232	9.15	0.224	8.72
unemp(la)					0.001	0.36	0.000	0.17
uman(la)					-0.006	-1.48	-0.006	-1.45
comp							0.075	2.96
tech							0.138	1.65
grammar							0.165	4.82
indep							0.192	3.57
singsex							0.031	1.36
special							0.003	0.03
Log-Lik.	-1982.18		-1419.99		-1193.69		-1174.53	

exam success, this reduces the effects of family background variables, indicating that past performance is related to background variables in the same way as the staying on decision. Including these variables mildly reduces the effect of the pupil teacher ratio, and it remains strongly significant. In column 3, we add parental preference variables as well as local labour market indicators. This hardly affects the coefficient of the variable PTRATIO. As expected, parental interest and parental preferences have a strong effect on the staying on decision. The local labour market indicators are insignificant.

Finally, in column 4 we add the school type variables. This reduces the size of the coefficient of PTRATIO, but, other than in the examination equation, this coefficient remains significant. Conditional on the type of school attended, an increase in the pupil teacher ratio by one standard deviation decreases the staying on probability by about 4.3 percent. Accordingly, the pupil teacher ratio appears to have a considerable influence on future career choices, even conditional on school type variables.

Again, the effects of the school type variables are quite strong, and reflect more than the mere difference in the pupil teacher ratios (reported in table 2a). The ordering of the parameter estimates is similar to that in the examination equation; pupils who attend grammar or independent schools have a 16 and 19 percentage points higher probability to stay on in full time education than pupils in the base category (modern schools). Here, the school type dummies may be capturing a number of effects. For example, peer pressure in grammar or independent schools may discourage teenagers from leaving school at the first possible opportunity. Furthermore, specialist staff employed to give informed advice about education and career choices may have an effect on school–leaving decisions.

School, Training or Work

We now turn to models which distinguish between the two alternatives to full time education, i.e. training and labour market participation. We have estimated multinomial logit models and generalised ordered probit models in which one of the cut off points is allowed to vary with the exogenous variables (see appendix). The latter model has the same flexibility as the multinomial logit model and avoids the assumption of independence of irrelevant alternatives, and we therefore report results for this model only. However, multinomial models basically led to the same conclusions.

We report results of the specification which corresponds to specification 4 in table 3, which includes school type variables. Table 4 displays the estimated marginal effects.

The effect of the pupil teacher ratio on the staying on decision is similar to that for the simple probit model. It increases the probability to enroll in training schemes, or to join the labour market, to equal parts, where the latter effect is significant only at the 10 percent level. To split up the non–education category reveals some further interesting details. For instance, while females do not differ significantly from males as regards their staying on decision, they tend to be much more likely to join the labour market than to enroll in some training schemes. In many other cases, the effects respect the expected ordering. For example, the test scores at age 11 have a positive impact on the probabilities of both states versus regular employment, with the effect on full time education much larger than that on training. Similar results hold for the family background variables and for parental preferences.

The models presented in tables 3 and 4 are reduced form specifications in the sense that they do not include examination performance as a regressor. We have estimated

Table 4: Career Decisions, Marginal Effects.

Decision:	Stay in School		Training		Labour Market	
Variable	Effect	t-ratio	Effect	t-ratio	Effect	t-ratio
oldsib	-0.040	2.80	0.001	0.07	0.039	2.77
yngsib	-0.010	1.18	-0.007	1.04	0.018	2.33
pawork	0.044	1.16	0.005	0.15	-0.050	1.37
paprof	0.121	2.80	-0.027	0.44	-0.093	1.47
mawork	-0.003	0.18	0.033	1.57	-0.029	1.36
female	-0.027	1.44	-0.187	9.87	0.215	10.86
paageft/10	0.145	2.40	0.077	1.02	-0.223	2.76
maageft/10	0.229	3.08	-0.086	0.94	-0.143	1.55
loginc	-0.020	0.69	0.003	0.12	0.016	0.52
room	0.054	1.68	0.009	0.34	-0.063	2.17
ptratio	-0.019	3.69	0.010	2.34	0.009	1.77
able7/10	0.021	3.10	-0.002	0.47	-0.019	3.05
able11/10	0.042	5.58	0.008	1.29	-0.051	7.17
intpar	0.065	2.86	0.019	0.98	-0.084	3.89
paruniv	0.443	18.18	-0.084	3.34	-0.359	13.97
paralev	0.231	9.50	-0.016	0.82	-0.215	9.14
unemp(la)	0.001	0.16	-0.013	2.56	0.012	2.44
uman(la)	-0.005	1.37	0.003	0.86	0.002	0.66
comp	0.066	2.60	-0.015	0.77	-0.051	2.28
tech	0.137	1.77	-0.022	0.22	-0.115	1.04
grammar	0.160	4.74	-0.212	4.42	0.051	1.08
indep	0.185	3.10	-0.021	0.28	-0.164	1.83
singsex	0.025	1.18	0.011	0.49	-0.036	1.54

Log-Likelihood: -7132.44

a number of structural models where we condition additionally on exam performance. The structural estimation results are insightful to access the robustness of our findings, and to investigate whether structural estimation changes the effect of the other parameter estimates. We estimate examination and continuation equations simultaneously by maximum likelihood (see appendix for details). Although we condition explicitly on previous ability test scores, therefore controlling for usually unobservable ability components, some unobserved heterogeneity may be left which affects both examination performance and career decisions. To account for potential endogeneity bias of examination performance in the career choice equation, we allow for correlation between the errors in exam success and career choice equations.

To identify this model without relying on the normality assumption of the error terms requires exogenous instruments that do not affect the career choice directly. We have experimented with two different identification strategies. First, we have included a set of 118 county dummies in the examination equation, but we have excluded these variables from the career choice equation. School expenditures in the UK are decided on county level, and county dummies should capture level effects of school quality. This is valid if variations in school expenditures, as reflected by the county dummies, affect career choices only indirectly via examination success, conditional on background variables and previous achievements.

Second, we use indicators of school absenteeism for reasons of illness in the year before the final examinations. Here our assumption for the validity of our instruments is that absenteeism affects career choices only indirectly via examination success. This seems reasonable as long as past health hazards are of an unforeseen and temporary nature – for instance, absenteeism because of flu, or a minor accident, may affect exam-

Table 5: Career Decisions, Marginal Effects of PTRATIO.

Decision:	Stay in School		Training		Labour Market	
Variable	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
	Identification: Normality; No School Types					
Total Effect	-0.0273	5.20	0.0149	3.442	0.0124	2.61
Direct Effect	-0.0235	4.72	0.0132	3.066	0.0102	2.16
Indirect Effect	-0.0038	2.33	0.0016	1.935	0.0022	1.52
	Log-Likelihood: -7175.88; ρ = -0.138; t-value = 1.95					
	Identification: Absenteeism; No School Types					
Total Effect	-0.0276	5.12	0.0147	3.23	0.0129	2.56
Direct Effect	-0.0225	4.50	0.0133	2.91	0.0092	1.84
Indirect Effect	-0.0051	2.60	0.0014	1.80	0.0037	2.04
	Log-Likelihood: -7159.98; ρ = -0.056; t-value: 0.85					
	Identification: County Dummies; No School Types					
Total Effect	-0.0327	5.82	0.0173	4.06	0.0154	3.05
Direct Effect	-0.0266	4.97	0.0151	3.57	0.0115	2.30
Indirect Effect	-0.0061	2.72	0.0022	2.08	0.0038	1.89
	Log-Likelihood: -7121.84; ρ = -0.107; t-value: 1.73					
	Identification: Absenteeism; School Types included					
Total Effect	-0.0175	2.85	0.0103	2.12	0.0072	1.38
Direct Effect	-0.0173	3.00	0.0102	2.13	0.0070	1.40
Indirect Effect	-0.0002	0.12	0.0001	0.11	0.0002	0.12
	Log-Likelihood: -7100.34$\rho = -0.028$; t-value: 0.43					

ination performance, but, conditional on exam scores, should not have a direct effect on career choice. However, if health problems which have affected school attendance, are more permanent, they may also affect career choices in a direct manner, even after conditioning on past examination performance. In this case, our instruments would be invalid.

Finally, we also estimate models which rely on normality for identification only.

Our results under the various identification assumptions are quite similar and similar to those in table 4. Table A1 in the Appendix presents the model in table 4 including exam performance, where absenteeism variables are used as instruments. Comparing the reduced form and the structural specifications shows that conditioning on exam success reduces most other coefficients in magnitude, but does not change any of the qualitative conclusions. The effect of examination performance on the staying on decision is, as expected, positive, but quite moderate in size. The effect of the pupil teacher ratio on the probability to stay on at school is significantly negative.

Table 5 summarises the main results for the various specifications. The first model is nested in the other three. Likelihood ratio tests show that the absenteeism variables are jointly significant in the exam success equation, while the county dummies are not. The correlation between the unobservables is negative, but exogeneity of examination performance is not rejected in all cases. We have decomposed the total effect of the pupil teacher ratio on the three decisions (corresponding to the effect in the reduced form equation) into a direct effect and an indirect effect via examination performance. Point estimates of the marginal effects and t-statistics are also presented in table 5 (see appendix for calculation), for the various specifications.

The first three panels display results when school type variables are excluded, for the three specifications. The first row reports the total effect; in the next two rows, the total effect is broken down into its direct and indirect components. The effect of the pupil teacher ratio is quite similar in the three cases. The total effect is strongly significant. An increase in the pupil teacher ratio by one standard error decreases the probability that the child stays on at school by 6 to 7 percentage points. The indirect effect is significantly different from zero, but it contributes only to one fourth of the total effect.

The last panel reports results when school type variables are included, where absenteeism is used for identification. The indirect effect of PTRATIO now drops to zero, as expected from the results in table 2, and the direct effect is reduced in size. Both the direct and the total effect of the child teacher ratio on the choice for full time education remain significantly negative.

5 Conclusion

We investigate the effect of school quality measures on exam success and career choices of 16 year old school children. Accordingly, we examine the effects of school input on performance and career decisions at a particularly early stage of the students' career. We find that, conditional on parental background information and the teenager's past performance, the pupil teacher ratio has a significant and negative effect on examination performance. The British school system distinguishes between various school types, among them selective and non-selective schools. If we condition on school type variables, this effect of the pupil teacher ratio becomes insignificant.

As for career choices, we focus on the decision at age 16. For an analysis of the impact of the quality of secondary schools, this seems a more direct approach than looking at the ultimate level of education attained. We conclude that the impact of rising pupil teacher ratios is perhaps much more important than previously thought. We find that teenagers in schools with high pupil teacher ratios have a larger probability to drop out of school at age 16. This effect prevails even when controlling for school types and when conditioning on previous exam performance. It is also robust for the type of model that is used. Thus, an increase in pupil teacher ratios is likely to affect far more than just educational performance, if the more long term issues are considered. These results are in line with earlier findings by Card and Krueger (1992), who use state level data for the U.S. and find that a decrease in the pupil-teacher ratio increases the average length of education.

6 References

- Altonji, J. G. and T. Dunn (1996): " Using Siblings to Estimate the Effects of School Quality on Wages," *Review of Economics and Statistics*, 78, 665–685.
- Becker, G.S (1981): *A Treatise on the Family.* Cambridge: Harvard University Press.
- Behrman, J.R. and P. Taubman (1986): "Birth Order, Schooling and Earnings," *Journal of Labor Economics*, 4, 121-45.
- Betts, J. (1995): " Does School Quality matter? Evidence from the National Longitudinal Survey of Youth," *Review of Economics and Statistics*, 231-250.
- Card, D. and A.B. Krueger (1992): "Does School Quality Matter?," *Journal of Political Economy*, 100, 1-40.
- Card, D. and A.B. Krueger (1996): " School Resources and Student Outcomes: An Overview of the Literature and New Evidence from North and South Carolina," *Journal of Economic Perspectives*, 10, 31-51.
- Coleman, J.S., et al. (1966): *Equality of Educational Opportunity* Washington DC, US GPO.
- Dearden, L., J. Ferri and C. Meghir (1998), "The Effect of School Quality on Educational Attainment and Wages," *mimeo*, Institute of Fiscal Studies, London.

- Feinstein, L. and J. Symons (1997): "Attainment in Secondary School," *Discussion Paper*, 341, London School of Economics.

- Goldhaber, D. D. and D. J. Brewer (1998): " Why don't Schools and Teachers Seem to Matter?," *Journal of Human Resources*, 32, 505-523.

- Hanushek, E.A. (1992): "The Trade Off Between Child Quantity and Child Quality," *Journal of Political Economy*, 100, 84-117.

- Hanushek, E.A. (1996): " Measuring Investment in Education," *Journal of Economic Perspectives*, 10, 9-30.

- Hanushek, E.A., S. G. Rivkin, L.L. Taylor (1996): "Aggregation and the Estimated Effects of School Resources," *Review of Economics and Statistics*, 78, 611 – 627.

- Harmon, C. and I. Walker (1997): "Selective Schooling, School Quality, and Labour Market Returns," *mimeo*, University College Dublin.

- Heckman, J., A. Layne-Farrar, and P. Todd (1996): " Human Capital Pricing Equations with an Application to Estimating the Effect of School Quality on Earnings," *The Review of Economics and Statistics*, 78, 562-610.

- Johnston, G. and Stafford F. (1973): "Social Returns to Quantity and Quality of Schooling," *Journal of Human Resources*, 8, 139–155.

- Micklewright, J. (1986): "A Note on Household Income Data in ncds3," ncds *user support working paper* , 18, City University, London.

- Pradhan, M. and A. van Soest (1995): "Formal and Informal Sector Employment in Urban Areas in Bolivia" *Labour Economics*, 2, 275-298.

- Robertson, D. and J. Symons (1996): "Do Peer Groups Matter? Peer Groups versus Schooling Effects on Academic Attainment," *mimeo*, London School of Economics.

Appendix: Structural Model, Likelihood Contributions, and Marginal Effects

We model the number of O' level passes obtained at age 16 as a censored regression equation:

$$E_i^* = A_{Ei}\,\beta_E \,+\, u_{Ei}\,; \;\; E_i = \max(E_i^*, 0)\,. \tag{2}$$

Here E denotes the number of O' levels achieved, E^* is a latent variable, A_E is a vector of explanatory variables, and u_E is an error term.

The choice between continuing full-time education ($C16 = 2$), going into a training programme ($C16 = 1$), and entering the labour force ($C16 = 0$) is modeled as an ordered response:

$$C_i^* = A_{Ci}\,\beta_C \,+\, \gamma_C\, E_i \,+\, u_{Ci}, \tag{3}$$
$$C_i = 0 \text{ if } C_i^* < 0,\; C_i = 1 \,\text{if}\, 0 < C_i^* < m_{C_i},\; C_i = 2 \text{ if } C_i^* > m_C\,.$$

Here C_i^* is a latent variable, A_{Ci} is a vector of explanatory variables, and u_C is an error term. In a structural specification, the index C^* depends on exam success, with coefficient γ_C. In the standard ordered probit model, the category bound $m_C > 0$ is estimated as an additional parameter. We allow m_C to depend on all explanatory variables in the equation:

$$m_{Ci} = exp(A_{Ci}\,\beta_m \,+\, \gamma_m\, E_i\,)\,. \tag{4}$$

This leads to a model with the same degree of flexibility as the multinomial logit model, in which the alternatives are not ordered (cf. Pradhan and Van Soest (1995) for a comparison of the two in a similar framework).

The error terms u_E and u_C are assumed to be independent from all explanatory variables and bivariate normally distributed. By means of normalisation, we set $\text{Var}(u_C) = \sigma^2_{u_C} = 1$. The correlation between the two errors, $\text{Corr}(u_C\,, u_E)$, is given by ρ. For the structural model, we include exam outcomes as additional regressors in (3) and (4).

Likelihood Contribution

We only present the likelihood contributions of individuals with $C16 = 1$ (training scheme). Likelihood contributions of those with $C16 = 0$ or $C16 = 2$ are derived in a similar manner. We distinguish two cases:

1): $E = 0;\; C = 1$.

The likelihood contribution is given by

$$\begin{aligned} L &= P\{E^* < 0,\ 0 < C^* < m_C\} \\ &= P\{u_E < -X_E\,\beta_E\,, -X_C\,\beta_C\ < u_C\ < m_C - X_C\,\beta_C\,\}\,. \end{aligned} \tag{5}$$

For m_C, the expression in (4) can be substituted.

2): $E = E^* > 0;\ C = 1.$

Denote the residual in the exam equation by $e_E = E - X_E\,\beta_E$. Then the likelihood contribution is given by

$$\begin{aligned} L &= f_{E^*}(E)\ P\{0 < C^* < m_C|E\} = \\ &= f_{u_E}(e_E)\ P\{-X_C\,\beta_C\ - \delta_C\,E < u_C\ < m_C - X_C\,\beta_C\ \ - \delta_C\,E|\ u_E = e_E\} \end{aligned} \tag{6}$$

Here f_{E^*} and f_{u_E} are the univariate normal densities of E^* (conditional on exogenous variables) and u_E.

We use the BFGS algorithm in GAUSS to maximize the likelihood, and computed the standard errors from the outer products of the scores.

Marginal Effects in School Leaving Equation

The computation of the marginal effects presented in Tables 4 is based on (3) and (4). For notational convenience, we write $Z_C = (X_C, E)$, $\theta_C = (\beta'_C, \delta_C)'$, and $\theta_m = (\beta'_m, \delta_m)'$. We then have

$$\frac{\partial P[C = 0|Z_C]}{\partial Z_C} = -f_{u_C}(-Z_C\theta_C)\theta_C, \tag{7}$$

$$\frac{\partial P[C = 1|Z_C]}{\partial Z_C} = f_{u_C}(-Z_C\theta_C)\theta_C + f_{u_C}(m_C - Z_C\theta_C)\,[m_C\,\theta_m\ - \theta_C], \tag{8}$$

$$\frac{\partial P[C = 2|Z_C]}{\partial Z_C} = f_{u_C}(m_C - Z_C\theta_C)\,[\theta_C - m_C\,\theta_m]. \tag{9}$$

Since the marginal effects are functions of the parameters, the standard errors of their estimates can be computed from the standard errors of the parameter estimates (taking the distribution of Z_C as given). This can in principle be done by the delta method. A computationally easier alternative is to use simulations. The standard errors in the tables are computed as the standard deviations in samples of 500 marginal effects, computed from 500 draws of the vector of parameters from the estimated asymptotic distribution of the vector of parameter estimates.

The total and indirect effects in the structural form equations and their standard errors (Table 6) are computed in a similar manner. We simply substitute the terms with the inner derivatives in (7) – (9) by the appropriate expressions, corresponding to the total and indirect effects.

Table A1: Career Decisions, Marginal Effects.						
Decision:	Stay in School		Training		Labour Market	
Variable	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
oldsib	-0.030	1.89	-0.003	0.22	0.033	2.20
yngsib	-0.004	0.45	-0.010	1.25	0.014	1.83
pawork	0.029	0.70	0.010	0.29	-0.039	1.06
paprof	0.094	2.18	-0.026	0.44	-0.067	1.08
mawork	0.004	0.18	0.031	1.56	-0.036	1.63
female	-0.027	1.43	-0.187	9.76	0.214	10.85
paageft/10	0.102	1.71	0.071	0.97	-0.173	2.15
maageft/10	0.199	2.59	-0.101	1.14	-0.098	1.01
loginc	-0.004	0.13	-0.003	0.13	0.007	0.27
room	-0.044	1.36	-0.015	0.58	0.060	2.10
ptratio	-0.017	3.00	0.010	2.13	0.007	1.40
able7/10	0.016	2.24	-0.003	0.64	-0.012	2.07
able11/10	0.011	1.16	0.017	2.66	-0.028	3.09
intpar	0.040	1.60	0.029	1.48	-0.069	2.99
paruniv	0.390	13.34	-0.084	3.09	-0.306	9.46
paralev	0.228	8.91	-0.020	0.88	-0.207	8.40
unemp(la	0.001	0.16	-0.014	2.42	0.013	2.33
um(la)	-0.005	1.32	0.003	0.79	0.002	0.63
comp	0.052	2.05	-0.021	1.00	-0.031	1.54
tech	0.122	1.50	-0.006	0.06	-0.116	1.16
grammar	0.082	2.13	-0.205	4.35	0.123	2.34
indep	0.131	2.16	-0.003	0.04	-0.127	1.42
singsex	0.021	0.92	0.008	0.34	-0.029	1.26
exam	0.054	5.35	-0.008	1.30	-0.046	3.57
Log-Likelihood: -7100.34; ρ = -0.028; t-value = 0.43						
Instruments: Absenteeism.						